ROBUST CT IMAGES NOISE REDUCTION USING WAVELET AND CONTOURLET TRANSFORM

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Abstract- Noise is one of the most important challenging variables in medical imaging. Picture denoising refers to the enhancement of a medical digital image contaminated with Additive White Gaussian Noise (AWGN). Different types of noises may impact a digital medical image or video. Impulse noise, Poisson noise and AWGN these are different types of noises. Because of the noise, computed tomography (CT) images are of low quality. The quality of CT images depends directly on the absorbed dose in patients in such a way that the increase in absorbed radiation, thus the absorbed patient dose (ADP), increases the quality of CT images. In this manner, noise reduction techniques on purpose of images quality enhancement exposing no excess radiation to patients is one the challenging problems for CT images processing. Noise reduction in CT images was performed in this work using two distinct 2-dimensional (2D) directional transformations, i.e. Contourlet and Discrete Wavelet Transform (DWT), compared to each other and we proposed a new threshold in wavelet domain for not only noise reduction but also edge retaining, consequently the proposed method retains the modified coefficients significantly that result good visual quality. Data evaluations were accomplished by using two criterions; namely, peak signal to noise ratio (PSNR) and Mean Square Error (MSE).

Keywords-Denoising, CT, Wavelet, Contourlet, PSNR, MSE.

1. INTRODUCTION

During image transmission or recording, many sorts of noise will have an effect on any image. Additive White Gaussian Noise (AWGN), salt and pepper noise and speckle noise square measure some types of influenced noise, etc. While not moving image characteristics, the role of denoising is to eradicate such noise. victimisation Wiener filtering, the classical thanks to accomplish denoising is through linear process. Even so, variety of literatures have recently been revealed victimization of non-linear process, like thresholding is a very neseccary rework of domain wherever tiny coefficients square measure set to zero below an exact threshold [1]. Threshold denoising, however, needs a balance between the flexibility to suppress noise and loosen image characteristics. This loss happens within the sort of image blurring because of the loss of some giant pixels within the method of thresholding. associate reconciling ripple thresholding technique was instructed, wherever the edge price of the whole image is changed per the image energy determined from the spacial domain [2].

By analytical signal process of attenuated radiation exposed to the body, CT images square measure ultimately transmitted. Initially, there square measure many factors influencing accumulative noise, starting from radiation supply, beam line diversion, radiation attenuation within the body, backscattering radiation, detector sensitivity to image reconstruction. Of all CT images, absorbed radiation is that the most vital noise think about detectors [3]. The upper exposure the detectors get, the PSNR is obtained within the noninheritable CT images, so achieving higher image quality. However, the absorbed patient indefinite quantity will be enhanced, that has restricted the acquisition of high-quality images considering CT scan technologies have frequently mature enormously globally. Therefore, researchers have even additional seriously studied on various CT patient dose surveys are performed in varied countries and regions, with a variable pose on CT applications [4].

In this respect, reduction in CT imagess has been applied not solely to ensure safety issues, however additionally to preserve high CT image quality across many completely different ways. several of those techniques square measure supported hardware advances, like rising the performance of detectors and victimization phased array detectors, whereas others square measure manipulating software system, together with image reconstruction (IR) or Fourier back projection (FBP). In follow, noise reduction by manipulating radiation exposure is also achieved by increasing voltage, current or exposure time, each contributory to Associate in Nursing improvement. In additional general, image process techniques and software system ways at lower prices than hardware solutions can give high-quality images with no a lot of radiation exposure. Compared to the ripple thresholding method, noise reduction and quality improvement of CT images were achieved by victimization 2nd Curvelet and Contourlet transformations during this work.[31]

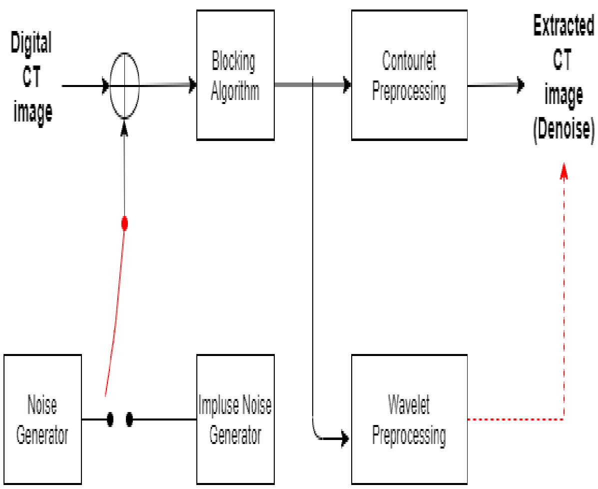

Figure 1: Proposed methodology

In this paper, the figure 1 shows the major conception aimed is to divide the image into many blocks and set a selected threshold for every block. In such a case, if the image contains a wide dynamic energy spectrum over blocks, then blocks containing bigger energy could have a smaller threshold to preserve image characteristics, whereas blocks containing less energy could have a bigger threshold to get rid of also as noise elements. In (MRI) and different medical images, the case of wide dynamic vary of energies over blocks is extremely frequent.

The rest of this paper is structured as follows: Section 2 describes briefly the medical image noise literature survey, Section 3 explains the proposed technique of image noise reduction using Computed Tomography (CT), Section 4 presents the specifics of the proposed methodology, Section 5 presents the results of the simulation, and the paper is concluded in Section 6.

2. LITERATURE SURVEY

The previous work concerned in CT pictures with denoising is in short mentioned during this chapter. The image is filtered mistreatment the 7X1 and 1X7 kernel vary filters and filtered images square measure another along to urge the image's edge. To exclusive the image and to boost the sides of the image, the Gaussian low pass filter and gradient magnitude square measure used. The input image and also the Gaussian filtered image square measure another to the fusion law. the first image and also the Gaussian image were consolidated to attain higher texture sweetening. By fusing the gradient magnitude image with the first image, the simplest edge sweetening is achieved [5].

A denoising technique which might be used with unrelated noise for 2 similar pictures is usually recommended. Noise within the initial input image is eliminated mistreatment the non-local suggests that filter during this denoising method, and a moving ridge packet thresholding technique is employed to get rid of noise within the second image. The output because of the filter provides excellent noise suppression, however it'd not be right to recover the tiny details of the input image. The moving ridge packet thresholding technique is employed to retrieve tiny data of the input image mistreatment correlation. For noise reduction and protection of structure, this approach is phenomenal [6].

Using Haar moving ridge transformation for brain pictures is recommended within the Denoising system. Merging 2 brain images collected mistreatment 2 separate modalities is image fusion to boost the brain pictures. Mistreatment carriedout the calculation changes in Haar moving ridge transformation has shown effective output associated with denoising parameters [7].

A low-rank thin element de-composition and wordbook methodology of learning for fusion, denoising and up the standard of medical pictures has been developed. Specifically, low-quality and thin regularization square measure utilized in the model of enhanching the methods of the learned models. Additionally, the thin portion is made within the image decomposition model employing a weighted nuclear norm and thin constraint to attenuate noise and reserve textural information. Finally, merging the low-quality and thin parts of the supply pictures obtains the consolidated image [8].

The use of fractional differential and directional derivatives is better during a medical image improvement method. within the construction of the masks, this approach relies on the image edge, transparency, texture details and structural characteristics of various pixels, further because the directional by-product of every element. this method enhances each the image's high frequency content and low frequency content. Finally, the feel data of the image is improved by this method [9].

In [10], prompt a reconstruction system of PWLS (penalized weighted least squares) mistreatment Union of Studied TRAnsforms (PWLS). The union of the square transforms is meant from several image patches taken from CT images. By switch between a agglomeration purpose, a thin cryptography, and a CT image reconstruction step, the PWLS-based value perform is increased. To recreate the CT image reconstruction, a Lagrangian technique with ordered-subsets is employed to decrease the forward and back projections. this system greatly improves the reconstructed image quality as compared with PWLS with a non-adaptive edge conserving regularizer reconstruction for each low-dose and normal-dose levels. Compared to one learned square rework, this approach provides higher leads to image reconstructions. once PWLS is made mistreatment weights supported patches, image quality and image uniformity resolution will be increased [11].

A method for low-contrast CT image sweetening is recommended. The formula is as follows: DWT is applied to the image, then SVD is obtained from the LL sub-band, then an appropriate correction issue is employed to provide Associate in Nursing improved LL part, Then the inverse SVD is applied, then the LL sub-band image is hierarchical as low distinction and moderate distinction bands into 2 categories, then the adaptational dynamic gamma correction perform is applied and eventually the inverse DWT is applied [12-14].

3. CT IMAGE DENOISING METHODS

For image denoising [15-17], there are different methods present. Generally, image denoising can be performed in: I spatial domain methods and (ii) domain methods of transformation.

3.1 Spatial Domain Filtering

In the original noisy image, spatial domain filtering reduces noise by applying a spatial filter mask directly to all original input pixels.

3.2 Transform Domain Filtering

3.2.1 Wavelets

It is functions that are used to decompose images into components of various frequencies. Due to its localized frequency, sub banding, multi-resolution analysis, and time domain, wavelet transform is a technique for image processing applications.

3.2.2 Wavelet Transformed Based Denoising [18]

Two parameters are laid out to be in the DWT. Firstly, for decomposition, a wave perform is employed. The subsequent wave decomposition filter are often used for decomposition. Next, for thresholding all sub bands, the decomposition stage is chosen. The wave technique for the elimination of noise are often expressed as follows:

- The image's low frequency and high frequency coefficients square measure nonheritablevictimisation wave transformation.
- Test variation in noise.
- Thresholding is applied to careful parts.

Wiener filter (Linear filter) within the wave domain generates higher results once mathematician noise is gift within the image. Denoised image is obtained through the applying of Inverse wave Transformation. This filter, however, failed to yield visually united results, however the MSE was effectively reduced by the filtering operation.

3.2.3 Contourlet Transform (CT) Based Enhancement [19]

The CT is that the increased Contourlet transformation, which may solve the difficulty of whole creation among the improved curve image in a superb manner. additionally, choosing the output of the improvement and additionally the CT filter can directly influence the impact of image improvement.

The input image in disintegrates into the low-frequency domain and alternative high-frequency sub-bands. For the coefficients of the low frequency sub-band, linear transformation is taken into account. Reconciling thresholding technique is employed within the high-frequency sub-bands to eliminate noise. Then, NSCT's inverse is employed to recreate low and high frequency sub-bands into spacial domains. Finally, by unsharp masking, the fine details of the improved image area unit improved [20].

4. PROPOSED WORK

The proposed work of this research is explained in this section. The following section illustrates different strategies for denoising the CT images used in this research work.

4.1 Wavelet Transform

Wavelets is also used as a mathematical methodology to extract information from many different varieties, as well as - however positively not restricted to - audio signals and images. Generally, sets of wavelets are needed to totally analyze information. a set of "complementary" wavelets can interpret information while not gaps or overlaps so as to be mathematically reversible within the philosophical doctrine method [21]. In wavelet-based compression/decompression algorithms, collections of complementary wavelets ar thus helpful wherever it's fascinating to recover the first information with stripped-down loss. Continuous signal wavelet transformation is defined as, Where

$$[W_\psi f](a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\psi^* \left(\frac{t-b}{a}\right) dt \quad (1)$$

- b denotes time shift of wavelet and
- $*$ symbol denotes complex conjugate.
- a denotes wavelet dilation,

4.2 Decomposition To Lower Levels

The image is divided or rotten into four totally different levels once a image is subjected to riffle transformation: one. Approximation coefficients, 2.Vertical coefficients, 3. Horizontal coefficients, and 4. Diagonal coefficients. The constant of approximation includes a lot of image details than the opposite 3 coefficients. The divided image is then added to a threshold constant with a price of fifty and that we get the edge image as a consequence. once this method, the rotten image is reconstructed mistreatment the riffle remodel reverse method. For up to 3 stages, the decomposition method has been tested conjointly the} inverse method for identical 3 levels has also been performed [22-24].

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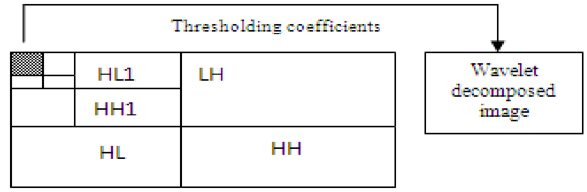


Figure 2: Decomposition of the given noise image.

When a image is subjected to a moving ridge remodel, the moving ridge decomposition takes place is shown in the figure 2. because the image is split into completely different elements, (i.e.) Lower Low (LL), Lower High (LH), Higher Low (HL) and High low (HL), the decomposition of the initial image takes place (HH). The approximation (a1), vertical (v1), horizontal (h1) and diagonal (d1) coefficients area unit so developed into four coefficients [25].

The figure 3 shows the frequency coefficients of the lower level area unit more divided into multiple levels (i.e.) LL2, LL3, etc. every has coefficients a, v, h and d of their own. the subsequent illustration of the decomposition is given.

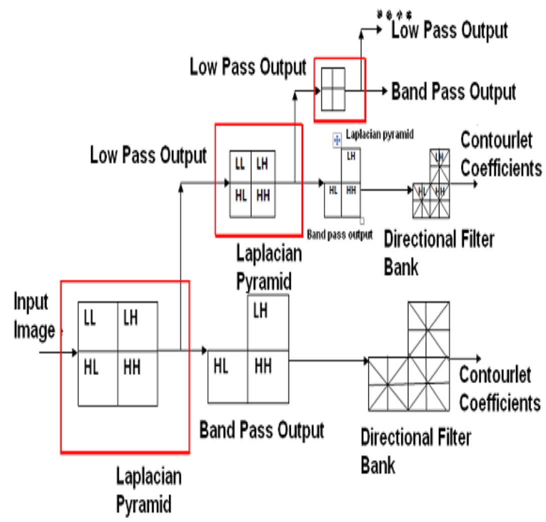


Figure 3: Decomposition of Wavelet Transform

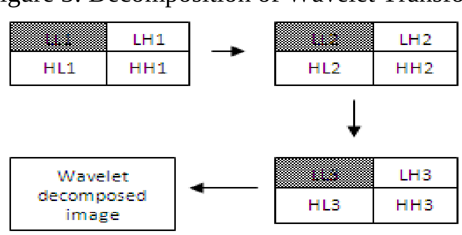


Figure 4: Decomposition of the Wavelet and Contourlet Transform using CT image

4.3 Contourlet Transform

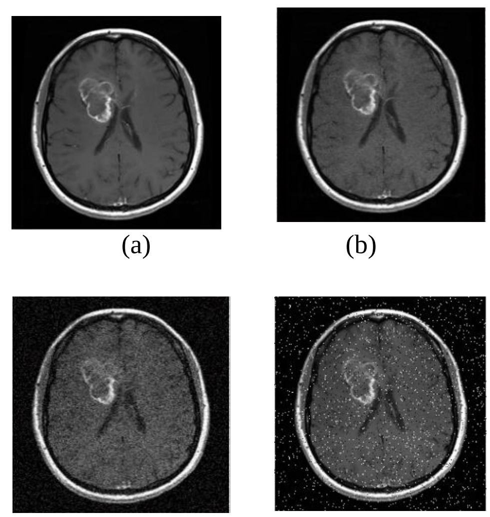
In capturing, the pure mathematics of image edges, the drawbacks of wide used divisible extensions of one-dimensional transformations, like the Fourier and rippling transforms, area unit well established is shown in figure 4. We tend to area unit seeking a "true" two-dimensional transformation during this paper which will capture the intrinsic geometric structure that's basic to visual information. In exploring pure mathematics in image, the most challenge comes from the separate original of the information. Thus, not like alternative approaches, like curvelets, that initial produce never-ending domain transformation so discretize sampled knowledge, our approach begins with a separate domain construction so studies its convergence to never-ending domain enlargement. Specially, exploitation non-separable filter banks, we tend to produce a discrete-domain multiresolution and multidirection enlargementin abundant identical approach as wavelets were derived from filter banks. Exploitation contour fragments, this construction leads to a flexible multi-resolution, local, and directional image enlargement, and is so referred to as the Contourlet rework [26]. For N-pixel pictures, the separate Contourlet rework includes a quick iterated filter bank algorithmic program requiring order N operations. Additionally, through a directional multiresolution analysis system, we tend to build an exact relation between the shaped filter bank and also the associated continuous domain Contourlet enlargement. We tend to show that Contourlets succeed the best approximation rate for piecewise swish functions with discontinuities on double endlessly distinguishable curves with parabolic scaling and adequate directional vanishing moments. Finally, in several image process applications, we tend to gift many numerical experiments showing the flexibility of Contourlets.

4.4 Threshold Based Approach

The threshold-based approach may be a modest, effective system with one or additional thresholds relative to its severity. As a rising threshold-based strategies are solely classes. Additionally, if a image has objects with an equivalent intensity or unsimilarity among extremely discourse objects, that the threshold remains the most effective selection for characteristic objects and backgrounds. Usually, threshold values with native applied mathematics properties like average MRI intensity with previous data ar evaluated. Moreover, the distribution of Gaussian was to assess the thresholds for common brain MRI images [27, 30].

5. RESULT AND DISCUSSION

This section discusses the significant various performances of various techniques involved in this proposed work.



(a) (b)

(c) (d)

Figure 5: CT image of Noisy image with AWGN (a), Salt & Pepper noise (b), Speckle Noise (c) and Poisson noise (d).

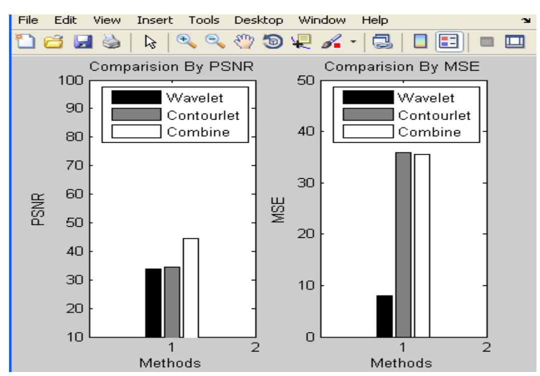


Figure 6: Comparison of different methods of PSNR and MSE

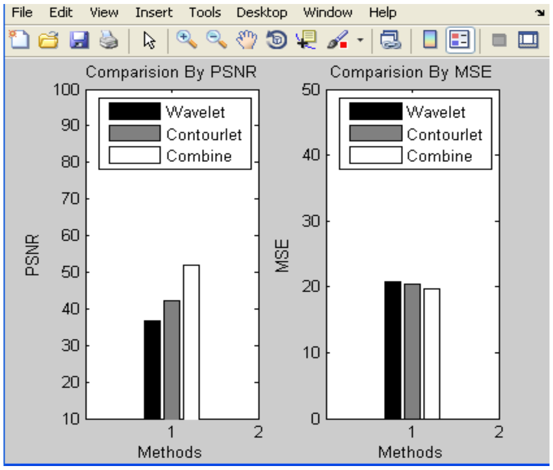


Figure 7: Comparison of different transforms for PSNR and MSE

Table 1: Mean Square Error (MSE) of using CT images

S.No	Techniques	MSE Values
1	Wavelet [28]	22.10
2	Contour [29]	20.05
3	Coimbined (Proposed)	18.00

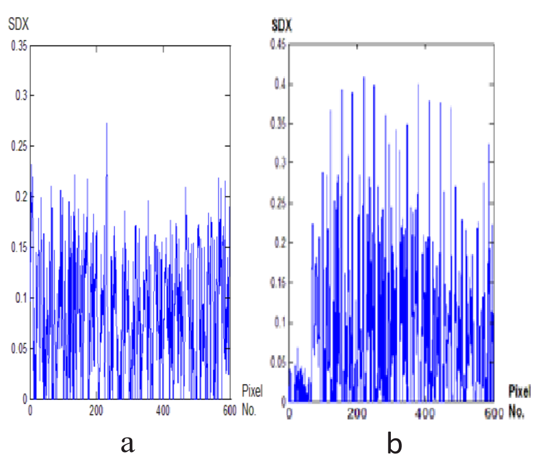


Figure 8:.SD (a)Barbara image (b) Proposed

Table 2: Comparison of PSNR values for different noises in CT images

Noises	Wavelet	Contourlet	Combined
Poisson	39.1361	62.9946	68.4056
Salt & Pepper	33.6751	34.2327	35.9905
Gaussian	36.5852	42.2214	51.7853
Speckle	37.9991	48.1547	57.4796

The figure 5 shows the CT image acquired from input with different noises has carriedout and it has been removed or denoise by thr proposed method of wavelet and countourlet transform. Likewise, the figure 6, 7 and 8 shows the different methods of denoising were used for the CT images measured by PSNR , MSE parameters and standard deviation. The tables 1, 2 and 3 shows the comparison various methods with proposed method for the parameters os MSE and PSNR using CT images.

Table 3: Peak Signal to Noise Ratio (PSNR) of using CT images

S.No	Techniques	PSNR Values
1	Wavelet [28]	37.09
2	Contour [29]	42.01
3	Coimbined (Proposed)	52.10

6. CONCLUSION

The reduction of CT noise is of great importance, however very challenging. Higher noise levels, the very low contrast, and also the retain the high frequency compose were enclosed within the sequenc of inflicting de-noising strategies to fail. Dividing the image into blocks has been shown to reinforce the denoising method wavelet transform or Contourlet transforms. Contourlet transformation de noising behavior, however, outperforms the wave behavior. Simulation outcomes on each normal and medical CT image showed that in medical magnetic resonance imaging imagess, the planned the interference approach is simpler than in normal pictures. The findings additionally showed that the denoising improvement depends on the scale of the block and also the lower the scale of the block, the larger the gain of PSNR. However, because of the little size of the Contourlet rework LL band, there's a minimum block size to be sized. The minimum size of the block depends on the scale of the initial image and also the range of levels remodeled by Contourlet. For the future work, the variable (adaptive) block size includes to operate on energy enclosed in every block space sizes for the effective PSNR.

REFERENCES

[1] Akshaya. K. Mishra, Alexander Wong , David. A. Clausi , Paul. W. Fieguth,"Adaptive Nonlinear Image Denoising and Restoration Using a Cooperative Bayesian Estimation Approach",,IEEE Transactions On Computer Vision, Graphics & Image Processing,Vol.1, pp.621-627,2018.

[2] Alexander Wong, Akshaya Mishra, Paul Fieguth, and David Clausi, "An Adaptive Monte Carlo Approach to Nonlinear Image Denoising", 19th International Conference on Pattern Recognition,2008.

[3] AnjaBorsdorf , Rainer Raupach , Thomas Flohr and Joachim Hornegger, "Wavelet based Noise Reduction in CT-Images using Correlation Analysis",IEEE Transactions On Medical Imaging, Vol.27,no.12,pp.1685 - 1703,2008.

[4] Arivazhagan,S.Deivalakshmi,S.AndKannan,K, "Performance Analysis of Image Denoising System for different levels of Wavelet Decomposition",The International journal of Multimedia & Its Applications, Vol. 6,no.3,pp.35-46,2014.

[5] P.S. Hiremath, Prema T. Akksaligar and Sharan Badiger, "Performance comparison of Wavelet Transform and Contourlet Transform based methods for Despeckling Medical Ultrasound Images", International Journal of Computer Applications Vol.26, no.9,pp.34-41, 2011.

[6] Joao M. Sanches, Jacinto C. Nascimento and Jorge S. Marques, "Medical Image Noise Reduction using the Sylvester – Lyapunov Equation", IEEE Transactions on Image Processing, Vol. 17, no.9,pp 1522 - 1539,2008.

[7] Louisa Lam, Seong Whan Lee and Ching Y. Suen, "Thinning Methodologies-A Comprehensive Survey", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 14, no.9,pp.869 - 885, 2009.

[8] Jean-Luc Starck, Emmanuel J. Candès, and David L. Donoho, "The Curvelet Transform for Image Denoising", IEEE Transactions on Image Processing, Vol. 11, no. 6, pp. 670 – 684, 2002.

[9] Minh N Do and Martin Vetterli, " An Efficient Directional Multiresolution Image Representation", IEEE Transaction On Image Processing,Vol.14,no.12,pp.2091-2106, 2005.

[10] S. G. Chang, B. Yu, and M. Vetterli, "Spatially adaptive wavelet thresholding with context modeling for image denoising", IEEE Trans. Image Process., Vol. 9, no. 9, pp. 1522–1531, 2000.

[11] S. G. Chang, B. Yu, and M. Vettereli, "Adaptive wavelet thresholding for image denoising and compression," IEEE Trans. Image Processing, Vol. 9, no. 9, pp. 1532–1546, 2000.

[12] A.W.M. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain, "Content-based image retrieval at the end of the early years," IEEE Trans. Pattern Anal. Mach. Intell., Vol. 22, no. 12, pp. 1349-1380, 2000.

[13] L. Zheng, A.W. Wetzel, J. Gilbertson, and M.J. Becich, "Design and analysis of a content-based pathology image retrieval system," IEEE Trans. Inf. Tech. Biomed., Vol. 7, no. 4, pp. 249-255, 2003.

[14] X. Xu, D. J. Lee, S. Antani, and L. R. Long, "A Spine X-Ray image retrieval system using partial shape matching," IEEE Trans. Inf. Tech. Biomed., Vol. 12, no. 1, pp. 100-108, 2008.

[15] H. C. Akakin and M. N. Gurcan, "Content-Based microscopic image retrieval system for multi-image queries," IEEE Trans. Inf. Tech. Biomed., Vol. 16, no. 4, pp. 758-769, 2012.

[16] M. M. Rahman, S. K. Antani and G. R. Thoma, "A learning-based similarity fusion and filtering approach for biomedical image retrieval using SVM classification and relevance feedback," IEEE Trans. Inf. Tech. Biomed., Vol. 15, no. 4, pp. 640-646, 2011.

[17] G. Scott and C. R. Shyu, "Knowledge-Driven multidimensional indexing structure for biomedical media database retrieval," IEEE Trans. Inf. Tech. Biomed., Vol. 11, no. 3, pp. 320-331, 2007.

[18] S. Murala and Q. M. J. Wu, "Local Mesh Patterns Versus Local Binary Patterns: Biomedical Image Indexing and Retrieval," IEEE Journal of Biomedical and Health Informatics, Vol.18, no.3, pp. 929-938, 2014.

[19] M. M. Rahman, P. Bhattacharya, and B. C. Desai, "A framework for medical image retrieval using machine learning and statistical similarity matching techniques with relevance feedback," IEEE Transactions on Information Technology in Biomedicine, Vol. 11, no. 1, pp. 58–69, 2007.

[20] R. Rahmani, S. A. Goldman, H. Zhang, S. R. Cholleti, and J. E. Fritts, "Localized content-based image retrieval," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 30, no. 11, pp. 1902– 1912, 2008.
[21] T. Ahonen, A. Hadid, and M. Pietikainen, "Face description with local binary patterns: Applications to face recognition," IEEE Trans. Pattern Anal. Mach. Intell., Vol. 28, no. 12, pp. 2037-2041, 2006.
[22] S. He, J. J. Soraghan, B. F. O'Reilly, and D. Xing, "Quantitative analysis of facial paralysis using local binary patterns in biomedical videos," IEEE Trans. Biomed. Eng., Vol. 56, no. 7, pp. 1864-1870, 2009.
[23] L. Sorensen, S. B. Shaker, and M. de Bruijne, "Quantitative analysis of pulmonary emphysema using local binary patterns," IEEE Trans. Med. Imag., Vol. 29, no. 2, pp. 559-569, 2010.
[24] X. Tan and B. Triggs, "Enhanced local texture feature sets for face recognition under difficult lighting conditions," IEEE Trans. Image Process., Vol. 19, no. 6, pp. 1635-1650, 2010.
[25] B. Li and M. Q. H. Meng, "Tumor recognition in wireless capsule endoscopy images using textural features and SVM-Based feature selection," IEEE Trans. Inf. Tech. Biomed., Vol. 16, no. 3, pp. 323-329, 2012.
[26] L. Yang, Student, R. Jin, L. Mummert, R. Sukthankar, A. Goode, B. Zheng, S. C. H. Hoi, and M. Satyanarayanan, "A boosting framework for visuality-preserving distance metric learning and its application to medical image retrieval," IEEE Trans. Pattern Anal. Mach. Intell., Vol. 32, no. 1, pp. 33-44, 2010.
[27] S. R. Dubey, S. K. Singh, and R. K. Singh, "Rotation and Illumination Invariant Interleaved Intensity Order Based Local Descriptor," IEEE Transactions on Image Processing, Vol. 23, no. 12, pp. 5323-5333, 2014.
[28] S. R. Dubey, S. K. Singh, and R. K. Singh, "Local Diagonal Extrema Pattern: A New and Efficient Feature Descriptor for CT Image Retrieval," IEEE Signal Processing Letters, Vol. 22, no. 9, pp. 1215-1219, 2015.
[29] S. R. Dubey, S. K. Singh, and R. K. Singh, "Local Bit-plane Decoded Pattern: A Novel Feature Descriptor for Biomedical Image Retrieval," IEEE Journal of Biomedical and Health Informatics, 2015.
[30] S. Murala, R. P. Maheshwari, and R. Balasubramanian, "Local tetra patterns: a new feature descriptor for content-based image retrieval", IEEE Transactions on Image Processing, Vol. 21, no. 5, pp. 2874-2886, 2012.
[31] S. Veni,"Image Processing Edge Detection Improvements And Its Applications",International Journal Of Innovations In Scientific And Engineering Research (IJISER),Vol.3,No.6,Pp.51-54,2016.